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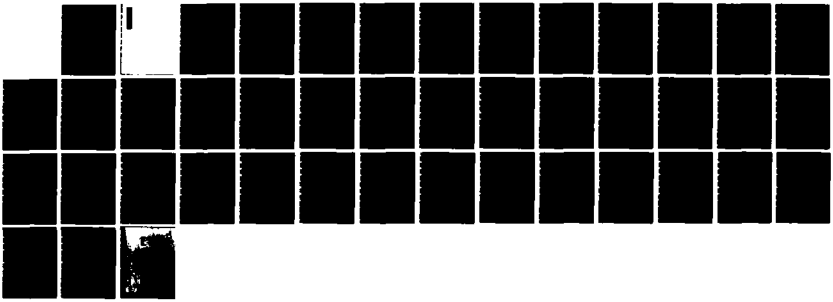

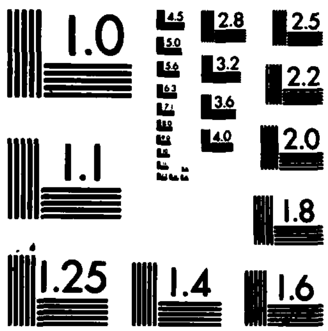

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Risk and Distributional Inequality

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This article was supported in part by a grant in cognitive science to the University of Chicago and to the University of Michigan from the Alfred P. Sloan Foundation and by Office of Naval Research Contract N00014-84-K-0065. I am grateful to Jonathan Baron, Jerry Busemeyer, Mary Douglas, Robin Keller, and Solomon Levine for discussions that were helpful in the early stages of this research, and to Robin Hogarth, Howard Kunreuther and Gregg Oden for their criticisms of an earlier draft of the paper. Requests for reprints should be sent to Lola L. Lopes, Department of Psychology, University of Wisconsin, Madison WI 53706.

In Press:
Journal of Experimental Psychology: Human Perception and Performance

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER WHIPP 20	2. GOVT ACCESSION NO. AD-A140373	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Risk and Distributional Inequality		5. TYPE OF REPORT & PERIOD COVERED Interim Report
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Dr. Lola L. Lopes		8. CONTRACT OR GRANT NUMBER(s) N00014-84-K-0065
9. PERFORMING ORGANIZATION NAME AND ADDRESS The Board of Regents of the University of Wisconsin System 750 University Ave., Madison WI 53707		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR197-079
11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research 800 North Quincy Street Arlington, Virginia 22217		12. REPORT DATE March 1984
		13. NUMBER OF PAGES 41
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE
16. DISTRIBUTION STATEMENT (of this Report) Approved for public release; distribution unlimited.		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)		
18. SUPPLEMENTARY NOTES		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) risk decision making distributions inequality		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) A "distributional model of risk" is described in which it is hypothesized that people's judgments of risk are similar to the kinds of judgments made in welfare economics concerning inequality of income distributions. The role played by the Lorenz curve in analyzing inequality is described and it is shown how Lorenz curves can be used to describe risks. Two hypotheses are presented concerning risk: first, that representing risks with Lorenz curves will be useful in capturing the salient psychological features of		

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risk; and second, that people's judgments of positive risks will be similar functionally to judgments of distributional inequality. Six experiments are presented that support the distributional model of risk for both preference judgments and judgments of riskiness. The implications of these experiments are described and the distributional model is compared with alternative models of risk.

S N 0102- LF- 014- 6601

Risk and Distributional Inequality

There are probably few psychological functions as important to conduct in uncertain environments as those that comprise the human system for analyzing and choosing among risks. This importance is reflected in the psychological literature by more than 30 years' research on the kindred topics of decision making under risk and risk measurement. The difficulty and subtlety of the topic, however, is made apparent by the fact that during this period no uniform picture has emerged for relating people's perceptions of and preferences for risk (cf. Coombs & Lehner, 1981; Luce, 1980; Payne, 1973). Indeed, it is fair to say that even such fundamental terms as *risk aversion* and *risk seeking* have no clear referents in psychological theory.

For present purposes, the literature on risk may be divided into two rough classes. In one class are risk analyses (most often aimed at accounting for risk preferences) that are couched in terms of the explicitly presented attributes of risky choices, i.e., the various outcomes that may occur and their associated probabilities. These approaches would include various theoretical treatments of risk based on the family of expected (or weighted) utility models (cf. Edwards, 1954c, 1961; Schoemaker, 1982) as well as more process oriented studies centered on how subjects actually select and use available stimulus information (cf. Payne, 1973; Slovic & Lichtenstein, 1968). In the other class are analyses (often aimed at risk measurement) that are based on higher order characteristics of the distribution of possible outcomes, particularly measures of dispersion such as variance or range and measures of asymmetry such as skewness. This group would include axiomatic approaches to risk measurement (Luce, 1980; Pollatsek and Tversky, 1970), empirical tests of portfolio theory (Coombs & Huang, 1970a,b; Coombs & Lehner, 1981), and laboratory studies of probability (skewness) and variance preferences (Coombs & Pruitt, 1960; Edwards, 1953, 1954a,b,d; Lichtenstein, 1965).

In evaluating the relative merits of these general approaches to risk, it is clear that the distributional approach has been the less successful of the two in accounting for either risk perception or risk preference (Coombs & Lehner, 1981; Lichtenstein, 1965; Payne, 1973). Yet, the view that distributional variables are important to risk is not only intuitive but is, as well, supported by the observation that the terms people use to describe risks in natural language (i.e., *long shot*, *almost sure thing*, *all or nothing*, etc.) typically refer to the shape of distributions. Indeed, one might easily agree with Allais (1952/1979) that sensitivity to the overall shapes of possible outcome distributions is "*the fundamental feature characterising the psychology of risk*" (p.54).

Are these intuitions simply wrong? Perhaps. But the view that is explored in this article is that approaches to risk based on distributions

have failed not because distributions are unimportant for risk, but rather because the particular distributional variables employed in these approaches -- typically higher order moments of distributions such as variance and skewness -- are unsuitable for capturing the psychologically relevant features of distributions. Instead, it will be argued that a distributional approach drawn from the field of welfare economics will provide a better framework in which to describe people's perceptions of and preferences for risk.

The Measurement of Inequality

In welfare economics, an important class of questions concerns how quantities such as income or wealth are distributed over members of a population. A formalism that has proven useful for describing such distributions is the Lorenz curve, which is simply a cumulative plot of the share of the quantity in question that is owned by cumulative segments of the population. The concept can be readily understood by use of an example from Atkinson (1975).

Insert Table 1 about here

Table 1 gives income distributions for the United Kingdom (U.K.), the Netherlands, and West Germany in the early 1960's. To take the U.K. as an example, we see that the poorest 10% of the population had only 2.0% of the total income for the U.K., the poorest 20% had only 5.1% of the total income, and so forth.

Insert Figure 1 about here

The panels of Figure 1 give the same data plotted as Lorenz curves. Percent of total income is shown on the ordinate and percent of total income units (i.e., families or individuals) is shown on the abscissa. Note that the functions curve downward from the main diagonal. This curvature is an indication that income is not uniformly distributed in the population. The further down a function curves, the greater the inequality of distribution and, conversely, the closer a function comes to the diagonal, the less the inequality.

The left panel of the figure compares the values for the Netherlands with those for the U.K. What is of interest in this comparison is that (looking back to Table 1) every cumulative segment of the population in the Netherlands has a smaller cumulative share of the total income than its counterpart in the U.K. This difference reveals itself graphically in that the Lorenz curve for the Netherlands lies everywhere below the curve for the U.K. Such a difference can be interpreted as showing that there is greater inequality of incomes in the Netherlands than in the U.K.

As it happens, however, the foregoing conclusion is not critically tied to the Lorenz curve formulation. In fact, when two distributions display

such a "nested" pattern, virtually any statistical measure of dispersion would lead to the same conclusion concerning relative inequality. These would include not only measures such as the variance that are familiar to psychologists, but also measures such as the Gini coefficient that are unique to welfare economics[1].

The nested pattern is, however, only one way in which Lorenz curves can be related. The right panel of Figure 1 shows that the Lorenz curves for West Germany and the U.K. cross over one another. Why this occurs is evident from the table. Notice that the very poorest West Germans have somewhat more of the total income than their counterparts in the U.K. -- 2.1% vs. 2.0%, 5.3% vs. 5.1%, and so forth. However, the moderately well-to-do classes in the U.K. are relatively better off than their West German counterparts.

Situations of this sort are interesting because it is not statistically obvious which of two intersecting Lorenz curves has the greater inequality. Thus, distributions which intersect might be identical in terms of some measure of dispersion, yet might not be judged to have the same degree of inequality. The difficulty, as Atkinson (1975) has argued, is that "<u>the degree of inequality cannot, in general, be measured without introducing social judgments</u>" (p. 47). In other words, contrary to what might be supposed, statistical measures such as the Gini coefficient or the variance are not "neutral" measures of inequality. Instead, "they embody implicit judgments about the weight to be attached to inequality at different points on the income scale....[Thus, in choosing a measure of inequality,] it may well be preferable to consider such values explicitly. Only then can it be clear just what distributional objectives are being incorporated as a result of adopting a certain measure" (Atkinson, 1975, pp. 47-48).

To illustrate, it might be argued on humanitarian grounds that in judging income inequality, greater weight should be attached to the bottom income groups than to the top income groups. (An extreme example of this viewpoint is given by Rawls, 1971.) Thus, it might be concluded that the U.K. has <u>greater</u> inequality of incomes than West Germany for the reason that its Lorenz curve lies <u>further from the diagonal in the low income ranges</u> and despite the fact that, statistically speaking, it has lower variance and also a smaller Gini coefficient.

Atkinson's (1970, 1975) approach to the problem of measuring inequality has been to create an index of inequality that introduces distributional objectives explicitly through a weighting parameter. Although this index has theoretical interest in the present context, it plays no role in the experimental presentation that follows. Thus, further discussion of the index can be deferred until the General Discussion. For the moment it suffices to summarize matters as follows: (1) in welfare economics, measurement of the inequality of income (or wealth) is made difficult by the fact that such judgments involve social values that, in general, are not captured by standard statistical measures of dispersion; (2) the particular features of income distributions that make statistical measures unsatisfactory for describing inequality become visually apparent when such distributions are plotted as Lorenz curves; and (3) measures of distributional inequality embody distributional objectives in terms of the relative weight given to inequality at different points on the income scale.

The Distributional Model of Risk

The central psychological premise in this article is that people's intuitions about risks are functionally similar to intuitions about distributional inequality. Although there are major differences between the domain of risk (in which decisions are made about outcomes attached to uncertain events) and the domain of welfare economics (in which issues of social and economic justice are formulated), both are concerned with procedures for selecting among distributional options. This section will show how the formal similarity between the two domains can be exploited to yield a structural representation that captures psychologically salient features of risky distributions.

Insert Figure 2 about here

The analogy between judgments of distributional inequality and judgments of risk can best be understood by concrete example. Consider a person who is offered the lottery shown in Figure 2. Each of the number signs (#) represents a lottery ticket. There are exactly 100 tickets, and the expected value of the lottery is $100. The dollar amount at the left of each row represents the prize that is attached to each of the tickets in that row. Thus, there is one ticket with a prize of $200, 7 tickets with prizes of $167 each, and so forth down to a single ticket with a prize of zero.

Insert Table 2 about here

Table 2 shows the same lottery information in the cumulative form that is used in plotting Lorenz curves. To make discussion simpler, the information has been presented for an idealized sample of 100 persons each of whom is assumed to have independently played the lottery once[2]. For the group as a whole, total winnings would amount to $10,000. Of this, 1 person (1% of cases) would win nothing, 8 persons (8% of cases) would win $33 or less giving them as a group .023 of the total winnings, 34 persons (34% of cases) would win $67 or less giving them .197 of the total winnings, and so forth.

Insert Figure 3 about here

These cumulative values are presented in Figure 3 as a Lorenz curve. As can be seen, this distribution, which has a fairly small dispersion, falls only a bit below the diagonal. The Lorenz curve for a "sure thing" in which everyone gets $100 would fall exactly on the diagonal, whereas the Lorenz curve for a more typical lottery in which most people win nothing and a few persons win large prizes would run along the abscissa for most of its length and then rise sharply to the upper right corner of the graph.

How should a person judge the risk of a lottery? It seems reasonable to suppose that under most circumstances (i.e., the drawing is fair, the tickets are randomly mixed, etc.) people should not assume that one ticket is any more likely to be drawn than another. In other words, from a normative perspective, people's beliefs about whether or not they are lucky should not affect their judgments about the riskiness of a lottery[3]. But to say that people's beliefs about luck should not affect their judgments is not to say that people should be indifferent to the dispersion of outcomes in the lottery, or even that they should weigh the various outcome positions equally. On the contrary, people may reasonably have distributional objectives that are better met by one distribution than another. Thus, they, like the welfare economists discussed above, may wish to weight outcomes differently at different points in the distribution.

The viewpoint taken here is that when people evaluate and choose among risks, they are, in some sense, choosing among the potential distributions of gain (or loss) into which they will be thrust after the risk is resolved. Thus, the central issue becomes: what kind of "rule" or "index" should a person use in "computing" the value of the risk such that the index captures the person's distributional objectives? The general hypothesis to be tested here, which I will henceforth refer to as the distributional model of risk, is that judgments of risk are functionally and psychologically similar to judgments of distributional inequality. In particular, the model embodies two propositions that lead to testable hypotheses about people's judgments of or choices among risks.

First, it is proposed that although risks may be presented to subjects as first order distributions, they are represented and processed in terms of their second order or cumulative properties. For example, a person might evaluate the lottery given in Figure 2 along the following lines: "If I play this lottery it is very unlikely that I would fail to win something, or even would win as little as \$33. Instead, it is much more likely that I would win \$67 or even more, although it would be unlikely for me to win as much as \$167." Note that the hypothetical evaluation process yields a set of inequalities each of which concerns the likelihood that the person will meet or exceed some particular outcome value, i.e., the likelihood of winning nothing versus the likelihood of winning "something," the likelihood of winning "as little as \$33" versus the likelihood of winning more, and so forth. If a process like this does occur then it is reasonable to suppose that a formalism for representing risks which emphasizes cumulative information will provide a good foundation for psychological theory. Thus, it is hypothesized that Lorenz curves, by virtue of their cumulative character, will be useful as a representational device for capturing those cumulative features of stimulus distributions that are salient to people when they judge or choose among risks.

Second, it is proposed that riskiness judgments for positive risks (i.e., distributions with all outcomes ≥ 0) are characterized by an enhanced weighting of the low end of the distribution. This enhancement is assumed to be functionally similar to that which occurs when a welfare economist, in judging the inequality of wealth or income in a population, chooses to emphasize the condition of those people who are least well off. Thus, it is hypothesized that the judged riskiness of lotteries which are equated for expected value reflects the degree to which the lottery has relatively many or relatively few poor outcomes. More specifically, it is hypothesized that

of two lotteries, the riskier lottery will be that one whose Lorenz curve lies furthest from the diagonal, particularly at the low end.

Experiments

The distributional model of risk was tested using positive lotteries in six separate experiments. Experiments 1 and 2 involved subjects' _preferences_ for lotteries, whereas Experiments 3 through 6 involved judgments of _riskiness_. All experiments were run using a pair comparison format in which a target set of stimulus lotteries was presented to subjects in all possible pairs and subjects were asked to choose which of the lotteries they would prefer to play (Experiments 1 and 2) or which of the lotteries was the more risky (Experiments 3, 4, 5, and 6).

All of the lotteries used in the experiments had multiple outcomes, ranging from 7 to 31 equally spaced prize levels. Such large numbers of outcomes are not usual in laboratory work on risk. Instead, two- or three-outcome bets tend to predominate. The multi-outcome stimuli were preferred for present purposes, however, since bets with small numbers of outcomes tend to confound stimulus factors such as skewness and probability of winning. As will be seen, there will be no need in interpreting the present results to assume that people process the many possible outcome values equally well, or even that they process them all. Nevertheless, it is worth noting that there was no indication that subjects found the stimuli to be confusing or difficult to process.

In the presentation that follows, Lorenz curves are used primarily as a pictorial device for describing the characteristics of people's preferences and judgments. Thus, there will be no need for indexing the Lorenz curves mathematically or for estimating a "risk parameter." However, there will be consideration in the General Discussion of how an index such as that proposed by Atkinson (1970, 1975) might be used to describe people's risk attitudes.

Experiments 1 and 2

Method

Stimuli. The stimuli for the experiments were thirteen multi-outcome lotteries (similar to the one in Figure 2) plus a sure thing of $100. All the lotteries had expected value equal to $100, but they had a variety of "shapes." The lotteries were presented to subjects in pairs as shown in Figure 4. Any particular lottery appeared equally often as "top" and "bottom" member of a pair.

Insert Figure 4 about here

Figure 5 shows the entire stimulus set. Although histograms are used in the figure to save space, lotteries were actually presented to subjects in the format shown in Figures 2 and 4. The "names" assigned to lotteries (in the first column of Figure 5) were chosen for mnemonic convenience. The histograms given in the second column show the general shapes of the distributions, the range of the prize values, the numbers of possible outcomes, and the relative numbers of tickets at each prize level. The Lorenz curve for each lottery is shown in the third column along with a coded designation of the name, and the mean and standard deviation of the lotteries are shown in the fourth and fifth columns, respectively. (For illustration, the lottery shown in Figure 2 is the "very peaked" lottery, the top lottery in Figure 4 is the "gradual positive skew / high variance" lottery, and the bottom lottery of Figure 4 is the "steep negative skew / low variance" lottery.)

Insert Figure 5 about here

The lotteries used in Experiment 1 are the first 10 lotteries in Figure 5 plus the sure thing of $100. The particular lotteries used are of no *a priori* importance, but it is useful to note that (a) all the lotteries include the possibility of a "zero" outcome, (b) there are both symmetrical lotteries and asymmetrical lotteries, and (c) the asymmetric lotteries come in pairs. For example, lotteries +G/HV and -G/LV are such a pair; they are identical in terms of the numbers of outcomes and the probabilities attached to the outcomes, but they are mirror reflected. Since the expected value is held constant at $100 and both lotteries are anchored at zero, the positively skewed lottery must be a high variance long shot with a small chance of a large prize while the negatively skewed lottery must be a low variance "short" shot with a relatively large chance of a moderately sized prize.

The stimuli for Experiment 2 comprised the same set of symmetrical lotteries and the sure thing plus the low variance negatively skewed lotteries. However, the high variance positively skewed lotteries were replaced by three analogous low variance positively skewed lotteries (+G/LV through +S/LV, respectively). As can be seen, these lotteries differ from the others in that their minimum prize is $58 or more.

Procedure. Subjects were run in groups of three to four in a small laboratory room. At the beginning of the session, subjects were given booklets containing the various stimulus pairs and they were told that the experiment was about their preferences concerning how chances are distributed over prizes in different kinds of lotteries. After showing the subjects several examples of lotteries and explaining how to read them, the experimenter described the task as follows:

> I want to be sure to emphasize that there are no right or wrong answers in this experiment. We are interested in your preferences about how chances are distributed over prizes. In fact, we designed all the lotteries so that they would be equivalent except

for how the chances are distributed. I'll explain what I mean. In statistics you learn that if a gamble or lottery is played many, many times, there will be some average amount of money per play that you can expect to win in the long run. This is called the "expected value" of the gamble or lottery. Each of these lotteries has an expected value of $100, which means that if you were allowed to play any of them for a long, long time, on the average you would win $100 per play. But, obviously, the lotteries differ from one another in terms of the amounts that a person is likely to win on a single play, and it is your preferences concerning these differences that we are interested in studying.

After it was clear that subjects understood the stimulus materials and the choice task, they were allowed to proceed at their own pace through the booklets. For each stimulus pair, subjects simply indicated whether they would prefer to play the "top" or the "bottom" lottery if they were given a single free play of either. The entire experiment took about 30 minutes.

Subjects. The subjects for Experiments 1 and 2 were 121 and 120 student volunteers, respectively, from University of Wisconsin and University of Chicago. They were approximately evenly distributed between males and females. Students from University of Wisconsin served for course credit. Those from University of Chicago served in exchange for pay.

Results and Discussion

The data for the experiments are simply the proportion of times that a subject chose a particular lottery out of the total number of times that the lottery was available for choice. Since each lottery was paired once with each of the other 10 stimuli (9 lotteries plus the sure thing), the maximum number of times that a lottery could be chosen was 10 and the minimum was zero. (Mean choice proportions for all six experiments are given in Table 3.)

Insert Figure 6 about here

Insert Table 3 about here

Figures 6 and 7 display the choice proportions as points on number lines that run from .00 to 1.00. Lotteries are indicated by coded Lorenz curves connected to the appropriate position on the number lines. Thus, the entries in the upper row of Figure 6 indicate that lottery +S/HV was chosen 25% of the time it was available, lottery +L/HV was chosen 30% of the time, and so forth. In each of the figures, data for Experiment 1 are displayed on the upper number line and data for Experiment 2 on the lower number line. For clarity, Lorenz curves for symmetrical lotteries are shown between the number lines while Lorenz curves for asymmetrical lotteries are shown above or below their respective number lines.

Insert Figure 7 about here

Since strong individual differences were to be expected in a preference task, it was convenient to group subjects according to the conventional criteria for risk aversion (i.e., the tendency to prefer a sure thing to an actuarially equivalent gamble) and risk seeking (i.e., the tendency to prefer a gamble to an actuarially equivalent sure thing). For purposes of statistical analysis, subjects have been labeled risk averse (see Figure 6) if they chose the sure thing 8 or more times out of the 10 occasions on which it was available. Likewise, subjects have been labeled risk seeking (see Figure 7) if they chose the sure thing three or fewer times. There were, for Experiments 1 and 2, respectively, 61 and 50 risk averse subjects and 22 and 25 risk seeking subjects. The data for the remaining 38 and 45 unclassified subjects will not be considered further[4].

Beginning with Experiment 1, it is apparent that the order of preference given by risk averse subjects (top line of Figure 6) is the same order given by inequality in the Lorenz curves. That is, risk averse subjects tended to prefer gambles with lesser inequality (i.e., Lorenz curves near the diagonal) to gambles with greater inequality (i.e., Lorenz curves bending far below the diagonal). More specifically, for symmetrical lotteries there was a significant tendency for preference to decrease monotonically as a function of inequality, $F(1,60) = 98.51$, $p < .01$. Likewise, asymmetrical lotteries with low inequality (i.e., negative skewness and low variance) were significantly preferred to their counterparts with high inequality (i.e., positive skewness and high variance), $F(1,60) = 39.46$, $p < .01$.

For risk seeking subjects (top line of Figure 7) the pattern of preferences is essentially reversed. There was a significant tendency for the high inequality asymmetric lotteries to be preferred to their low inequality counterparts, $F(1,21) = 6.60$, $p < .05$. Likewise, symmetrical lotteries with high inequality tended to be preferred to those with low inequality, although these data were highly variable and did not reach significance, $F < 1$.

Insert Figure 8 about here

The results of Experiment 1 are generally consistent with the hypothesis that risk preference is related to distributional inequality. However, the lotteries in Experiment 1 that had the most inequality also tended to have the greatest variance. Thus, it is not possible to say for sure whether subjects' preferences were due to inequality, or variance, or both. Experiment 2 removed this confounding by replacing the three high variance positively skewed lotteries by three other positively skewed lotteries that were matched for variance with their negatively skewed counterparts. A pair of such gambles is shown in Figure 8. Lottery pairs such as these are particularly interesting from the point of view of the distributional model since their Lorenz curves would cross over one another. Thus, one would predict that, if subjects' preferences for risk do reflect distributional inequality, their preferences for these two gambles should not be the same. In particular, risk averse subjects should prefer the bottom gamble (whose Lorenz curve lies closer to the diagonal at the low end) and risk seeking

subjects should prefer the top gamble (whose Lorenz curve lies closer to the diagonal at the top end.)

The data for Experiment 2 are shown on the lower scales of Figures 6 and 7. For risk averse subjects, the results clearly support the distributional model. The lotteries that are preferred are those have the least inequality for both symmetric [$F(1,49) = 26.85$, $p < .01$] and asymmetric [$F(1,49) = 4.97$, $p < .05$] cases. Note, especially, that in every analogous pair, the subjects preferred the positively skewed gamble with the non-zero minimum prize value to its negatively skewed, equal-variance counterpart.

For risk seeking subjects, however, the pattern seems to break down. Although preferences for symmetric lotteries generally increase with inequality, the effect is not significant, $F < 1$. Likewise, asymmetric lotteries seem to be mixed together with no apparent order, $F < 1$. However, inspection of the single subject data suggests that the lack of systematic effects was caused not by indifference or unreliability at the single subject level, but rather by strong disagreements between subjects about the desirability of the various lotteries. Since similar individual differences also occurred in Experiment 4, further discussion of this disagreement will be postponed.

In general, then, the results of both experiments support the distributional model, at least for risk averse subjects. However, the results of Experiment 2 have additional interest. In particular, the finding that people have strong differences of preference for lotteries that are matched in mean and variance but differ in skewness tends to rule out theoretical models of risk preference, such as the "quadratic utility function" proposed by Markowitz (1959) in which it is hypothesized that preferences for risk reflect only the mean and variance of the distribution of outcomes.

As a final note, it is interesting that for all four groups of subjects there appears to have been some tendency for the rectangular lottery to be more preferred than would be expected from Lorenz curve considerations alone. As will be seen, the data for Experiments 3 through 6 suggest that a similar "displacement" of the rectangular lottery also occurred for judgments of riskiness. This result is similar to Edwards' (1953; 1954a, 1954b) finding that subjects often appear to have a preference in two-outcome gamble situations for gambles in which the probabilities of the alternative outcomes are each .50. Anecdotal evidence bearing on this phenomenon will be presented at the end of the Results and Discussion section for Experiments 5 and 6.

Experiments 3 and 4

In Experiments 1 and 2, there were major differences of preference between risk averse and risk seeking subjects. Although the names "risk averse" and "risk seeking" suggest that these differences are due to differences in the subjects' *liking* for risk, it could well be that, in fact, the differences are caused by differences in how subjects judge the riskiness of the various lotteries. In other words, both groups of subjects might

suppose that they are choosing the least risky options. The purpose of Experiments 3 and 4 was to investigate the relationship between distributional inequality and subjects' judgments of riskiness.

Method

Stimuli and procedure. The stimuli for Experiments 3 and 4 were the same lotteries as were used in Experiments 1 and 2, respectively. The sure thing option, however, was omitted from the stimulus set. As before, the lotteries were presented to subjects in all possible pairs (45 pairs in each experiment).

The instructions were essentially like those for Experiments 1 and 2 except for the definition of the task. Subjects were instructed to ignore their personal preferences and to choose for each pair of lotteries whichever one they thought "most people" would say was the more risky.

Subjects. Subjects were, respectively, 87 and 101 student volunteers from the University of Wisconsin. All served for credit to be applied to their course grade.

Results and Discussion

The results of Experiment 3 are displayed on the upper scale of Figure 9. For both symmetric and asymmetric lotteries there is clear agreement that lotteries with high inequality are judged to be riskier than lotteries with low inequality; $F(1,86) = 38.68$ and 342.5, $p < .01$, for symmetric and asymmetric lotteries, respectively. In particular, the wide separation between the positively skewed lotteries and the negatively skewed lotteries suggests virtual unanimity among subjects concerning the relative riskiness of these stimuli. Thus, it seems unlikely that differences in preference between risk averse and risk seeking subjects were caused by disagreements about which lotteries are most risky.

Insert Figure 9 about here

For Experiment 4, however, the results are less clear. Although the riskiness of the symmetric lotteries tends to increase with inequality [$F(1,100) = 34.80$, $p < .01$], there is no apparent pattern in the data for the asymmetric lotteries. Although one might expect that the positively skewed lotteries would be judged least risky since their Lorenz curves lie nearer the diagonal at the low end, there was no significant difference in riskiness between positively and negatively skewed stimuli, $F < 1$. However, as was the case with the preference judgments in Experiment 2, the lack of significance in Experiment 4 appears not to be due to subject unreliability or stimulus nondiscriminability. Instead, there appears to be strong disagreement among subjects as to which of these lottery types is most risky.

Insert Figure 10 about here

The extent of this disagreement is made clear when subjects are divided on the basis of whether positively skewed lotteries were judged to be most or

least risky overall. The results are in Figure 10. As can be seen, 54 subjects supported the hypothesis that lotteries whose Lorenz curves lie nearest the diagonal at the low end will be judged least risky, $F(1,53) = 150.96$, $p < .01$. However, 47 subjects contradicted the hypothesis by judging these same lotteries to be most risky, $F(1,46) = 105.49$, $p < .01$[5].

In summary, then, Experiments 3 and 4 provide strong support for the hypothesis that judgments of riskiness are affected by distributional inequality, although the individual differences in Experiment 4 suggest that different processing mechanisms might be at work for the two groups of subjects. Despite this ambiguity concerning processing, however, there is clear evidence that lotteries with equal mean and variance, but with opposite skewness, are not considered to be equally risky. This result, which is in agreement with an earlier study by Coombs and Bowen (1971), suggests that theories of risk perception (e.g., Pollatsek and Tversky, 1970) in which risk is expressed as a linear function of the mean and variance of the outcome distribution can be ruled out.

Experiments 5 and 6

The strong individual differences in Experiment 4 were unexpected, but in retrospect seemed to be related to a problem that had arisen in an early pilot study. At that time, it seemed possible that subjects might have difficulty in judging what "most people" would consider to be risky. Thus, the task was put to them in terms of the $100 expected value. What was said was, "If you think it is more risky to pay $100 for the top lottery, choose it, and if you think it is more risky to pay $100 for the bottom lottery, choose it."

In running the first few subjects, it appeared that some paid a great deal of attention to the $100 reference point. Fearing that this might cause them to switch from processing the entire distribution to processing only a few values, the instructions were rewritten to the form actually used for Experiments 3 and 4. In retrospect, however, it seemed that stressing the $100 reference point might have affected the aspiration level of these pilot subjects and, hence, affected the perceived riskiness of the lotteries.

With respect to the individual differences in Experiment 4, then, it seemed possible that the two groups of subjects might differ in aspiration level, with the subjects who judged the positively skewed lotteries to be most risky having a higher aspiration level than subjects who judged these lotteries to be least risky. Inspection of Figure 8 will suggest why this might be. For subjects who aspire to win, say, $100 or more, the positively skewed gamble is risky since the probability of winning that much is fairly small. But for subjects who aspire to win only $70, the positively skewed lottery is riskless since it guarantees that the aspiration level will be met.

Experiments 5 and 6 examined the effects of the $100 reference point by resurrecting the instructions from the pilot study and using them with the same stimulus sets as Experiments 3 and 4. The subjects for the experiments were, respectively, 100 and 51 University of Wisconsin students who served for course credit.

Results and Discussion

The results of Experiment 5 are displayed on the top scale of Figure 11. For these stimuli, the mention of the $100 reference point has made essentially no difference in judged riskiness. As was the case with Experiment 3, risk tends significantly to increase with inequality for the symmetric lotteries, $F(1,99) = 113.07$, $p < .01$, and positively skewed high variance lotteries are judged to be significantly more risky than their negatively skewed low variance counterparts, $F(1,99) = 196.39$, $p < .01$.

This lack of effect of the reference point manipulation is entirely reasonable given the stimulus set in Experiment 5. That is, a subject who adopts an aspiration level of $100, say, is very likely to win $100 or more with the negatively skewed lotteries and very likely to win less with the positively skewed lotteries. Likewise, for the symmetric lotteries, the probability of winning noticeably less than $100 increases with inequality (or, what is the same in this case, with variance).

Insert Figure 11 about here

For Experiment 6, however, (lower scale on Figure 11) the manipulation has produced a clear effect, as can be seen by comparing the results with those for Experiment 4 (Figure 9). In contrast to the case for Experiment 4, there is now a noticeable and significant effect of skewness at the group level, $F(1,50) = 10.46$, $p < .01$, as well as a significant effect for the symmetric lotteries, $F(1,50) = 19.09$, $p < .01$. For these subjects, positively skewed lotteries that guarantee wins of $58 or more, but that are very unlikely to pay as much as $100, are viewed as riskier than negatively skewed lotteries that have the possibility winning zero but that are very likely to win $100 or more.

In summary then, the results of Experiments 5 and 6 support the hypothesis that the individual differences in Experiment 4 reflected differences between subjects in aspiration level. As will be indicated below, aspiration effects of this sort can be handled in the distributional model without difficulty.

As a final note, I would like to refer back to the observation that the rectangular lottery was generally judged to be less risky (and hence more acceptable to risk averse subjects) than its Lorenz curve would warrant. (No attempt will be made to test this conclusion statistically; visual inspection of the several graphs should suffice to show that something is going on with this stimulus.) A comment by a colleague following a conference talk on the distributional model is suggestive. The colleague said, roughly, "What I don't understand about the Lorenz curves is why the rectangular lottery is so unequal. If all the prizes have the same number of tickets, isn't the lottery distribution completely fair and equal?"

The point, obviously, is that inequality is not the same thing viewed cumulatively (i.e., in Lorenz curves) as when it is viewed in the first order probability distribution. It seems quite possible that some people might interpret such first-order equality as a form of "fairness." If so, they may

tend when they see a rectangular distribution to process it primarily in terms of this surface equality rather than in terms of the procedure they would use for other, less uniform lotteries.

General Discussion

Taken together, the six experiments support the distributional model of risk for preference judgments and for judgments of riskiness. In particular, the data (a) demonstrate the usefulness of the Lorenz curve formalism for representing psychologically significant differences among stimulus distributions and (b) support the hypothesis that, for some subjects at least, judgments of positive risks emphasize outcomes at the low end of distributions. However, it remains to be shown (c) how the model relates to the processing of risky choices, (d) how the model must be augmented to handle features of the risk domain that are not found in the welfare economic domain, and (e) why the model is preferable to other models of decision making under risk. These issues will be addressed briefly in turn.

Risk Processing

What determines the weighting of outcome levels? According to the present model, judgments of riskiness for positive risks are characterized by enhanced weighting of outcomes at the low end of the distribution. Such a weighting pattern might be interpreted psychologically as arising from either or both of two underlying causes: the pattern might reflect a general tendency for people to be pessimistic about risks (i.e., to believe that the worst *will* happen) or it might reflect the strategies they use for planning in the face of uncertainty.

There is no doubt that people often express pessimism, but it is unlikely that a bias toward expecting the worst could account for their risk preferences. Although such a bias might explain the prevalence of risk aversion for positive risks, there would be problems in accounting for the observation (dubbed the "reflection effect" by Kahneman and Tversky, 1979) that risk preferences tend to reverse when people are presented with negative risks, i.e., risks in which all outcomes are $\leq$ zero. To see why, consider again the lotteries in Figure 4. The large majority of people would prefer the bottom lottery to the top lottery. If, however, the potential gains were changed to potential losses, many people would switch their preference to the top lottery *despite the fact that it includes the potential loss of a very large sum*. Such a switch in preference would not be expected to occur if people systematically overemphasize the *worst* outcomes in a distribution[7].

A better interpretation of people's distributional preferences can be found by considering risk assessment to be a process of strategic planning based on guesses about plausible futures. For illustration, consider a person who is offered a choice between the lotteries in Figure 4 and suppose that the person would be satisfied to win $50 or more. The person might ask what prize amounts it would be "reasonable" to "plan on" winning if one or the other lottery were actually to be played. For the top lottery the chances of winning $50 or more are only moderate, 60%. For the bottom lottery, however, the chances of winning $50 or more are large, 90%. Thus,

the bottom lottery might be preferred since it is distributionally more plausible to expect that it will yield a satisfactory outcome.

For negative lotteries, however, the same plausible planning process might lead to switches in preference between the two lotteries. For example, suppose that in this obviously unpleasant situation, the person would be satisfied to get away with losing no more than $50. In the bottom lottery, fully 90% of people would lose $50 or more whereas in the top lottery only 60% would lose that much. Thus, the person might prefer the top lottery for losses since it is more likely to yield an acceptable outcome. But this is exactly the same consideration that led to a preference for the bottom lottery for gains[8].

In terms of the present model, then, differences in the weights attached to small and large outcomes reflect the fact that in considering shifts in our fortunes either up or down we tend to think in terms of distributional objectives. For example, someone like the person described above is likely to show the pattern of weighting for positive risks that is characteristic of risk aversion, i.e., a pattern in which the person apparently is willing to forego the opportunity to shoot for relatively unlikely large gains in exchange for a relatively certain shot at a smaller gain (i.e., $50).

<u>How does aspiration level affect risk processing</u>? The individual differences in Experiment 4 and the effects of the reference point manipulation in Experiments 5 and 6 suggest that the perception of risk depends critically on one's aspiration level. Kunreuther and Wright (1979) described an especially interesting illustration of such aspiration effects among subsistence farmers in Bangladesh. The example concerns small farmers with limited land holdings who must decide what proportion of their land to devote to food crops (which generally have lower expected return and also lower variance of return) and what proportion to devote to cash crops (which generally have higher expected return as well as higher variance).

Conventional wisdom has it that the smaller the farmer the larger should be the proportion of land devoted to the "less risky" food crops. However, there is empirical evidence that "in many cases, farmers with the smallest holdings of land plant a larger percentage of their land with cash crops than those with somewhat larger farms, often a percentage comparable to that of the very largest enterprises" (Kunreuther & Wright, 1979, p. 215).

It is easy to understand why high-income farmers are willing to risk planting a large proportion of the high-return, high-variance crop. But why are the lowest income farmers willing to gamble, particularly when loss of the gamble (i.e., crop failure) means that their families may go hungry? Kunreuther and Wright hypothesize that the nonmonotonicity in allocations of land to cash crops occurs because farmers use a <u>lexicographic preference order</u> for processing risks. Thus, although a farmer may wish to allocate his land so as to maximize his expected return, he may have certain minimum requirements that must be met before consideration of any other factor. For example, he must be able to plan on growing or buying a sufficient amount of rice to feed his family.

For the high income farmer, the minimum requirement is fairly easily met. Thus, the farmer can afford to devote a high percentage of land to the riskier cash crop. For the middle income farmer, the minimum requirement can only be met at the expense of sacrificing some degree of expected return

(planting a lower proportion of the cash crop) in order to obtain a concomitantly lower variance. These farmers can be said to follow a "safety first" principle. For the poorest farmers, however, there is no plan that guarantees satisfaction of the minimum requirement, even if nothing but food crops are planted. Thus, the low income farmer must accept an objectively higher level of risk than the middle income farmer and grow more of the cash crop.

How can such shifts in the aspiration level be accommodated within the distributional model? One possibility would be to model the degree of risk in an outcome distribution using the kind of index that Atkinson (1970, 1975) devised for measuring inequality. The index is given below:

$$\text{Inequality } (\underline{I}) = 1 - \left[\sum_{i=1}^{n} (Y_i/\overline{Y})^{1-\varepsilon} f_i \right]^{1/(1-\varepsilon)}$$

where Y_i is the income of those in the ith income range, f_i is the proportion of the population in the ith income range, and $\overline{Y}$ is the mean income. The parameter ε captures the weight attached by the society to inequality of incomes. It can run from zero, which means that society is indifferent to distribution, to infinity, which means that society only considers the condition of the lowest income group. (Strictly, the parameter cannot take the value unity since that would mean dividing by zero. Nevertheless, the index is well behaved as ε approaches unity from either side.)

To illustrate how Atkinson's index captures societal value judgments, consider again the income distributions in Table 1. For values of ε less than or equal to two, inequality is computed to be <u>less</u> in the U.K. than in West Germany. For values of ε equal to three or greater, however, inequality is <u>greater</u> in the U.K.

It is conceivable that an index modeled on Atkinson's might be used to describe risk attitude. In particular, the parameter ε might be useful for capturing not only whatever stable individual differences there are in risk attitude, but might also capture the shifts in risk attitude that accompany more temporary rises and falls in aspiration level[9]. One would expect, for example, that ε would tend to be high not only for naturally risk averse subjects, but also for risk seeking subjects under task conditions that induce low levels of aspiration. In situations, however, in which the person must for whatever reason seek a large gain (as presumably occurred for the poorest farmers in Bangladesh and for the subjects in Experiments 5 and 6 when the $100 reference point was used) the value of ε would be shifted downward (i.e., toward indifference for distribution) and the criterion for choice would shift toward maximizing the probability of meeting the aspiration level.

Extensions of the Distributional Model

The domain of risky options differs from that of income distributions in several important ways. To begin with, income is most often a positive quantity, whereas risks range over both positive and negative outcomes. In the case of negative risks (i.e., those with no outcomes > zero), it seems likely that the Lorenz curve analysis can be applied with no fundamental difficulty. However, for mixed risks (i.e., those that include both positive

and negative outcomes) the Lorenz curve formulation breaks down since it does not make mathematical sense to cumulate positive and negative values.

One possible solution for this problem is to model the positive and negative parts of a mixed risk separately and then combine the results. Although this procedure may seem *ad hoc*, separate consideration of gains and losses is not uncommon in applied work (Fishburn, 1977; Holthausen, 1981; Markowitz, 1959), and the notion that risk may be an additive function of a gain component and a loss component has been explored recently in psychology by Coombs and Lehner (1983).

Another theoretically interesting problem concerns how people judge the relative risks of distributions that differ in expected value. In the present experiments, distributions were constructed with equal expected values so that attention could be focused on distributional factors. In real life, however, choices must frequently be made between options that differ in expected value. These choices typically involve a trade off between something like the mathematical expectation of the option and some measure of the likelihood that a person will fail to reach his or her aspiration level (Allais, 1952/1979). It is the latter component that seems to be tapped by the distributional model. Further research will be necessary to determine the processing mechanisms that are employed in accomplishing the trade off.

Advantages of the Model

Although the distributional model does a good job of accounting for the present data, it should not be supposed that it is the only model that could do so. The family of expected utility models could do as well given proper choice of a utility function. Why, then, propose a new model of risk? The question is fair; to answer it, however, will first require that we ask what it means to have a *psychological* theory of risk.

The first theory of risk was developed by Daniel Bernoulli (1738/1967). He proposed that people evaluate risks in terms of the mathematical expectation of the *subjective* values of the various possible outcomes -- in other words, the expected *utility*. For Bernoulli, utility was a *psychological* construct capturing the common intuition that "*any increase in wealth, no matter how insignificant, will always result in an increase in utility which is inversely proportionate to the quantity of goods already possessed*" (p.25). Thus, the receipt of $100 would mean far more to a poor person than to a rich person. Put mathematically, money has marginally decreasing subjective value.

The critical insight of Bernoulli's theory was that for people with the kind of utility function that he proposed, the expected *utility* of a gamble would always be less than the utility of a *sure sum* equal to the gamble's expected value. Thus, Bernoulli was able to account for the prevalence of risk aversion. But twentieth century economists became disenchanted with the Bernoullian concept of utility (in part) because it was difficult to measure.

Interest in the expected utility model was rekindled, however, when von Neumann and Morgenstern (1947) published the second edition of *Theory of Games and Economic Behavior*. The critical factor in this resurgence of interest was that von Neumann and Morgenstern had devised a way to measure utility rigorously, by having people indicate their preferences among

different gambles. The problem, however, was that von Neumann and Morgenstern's "utility" was not the same thing as Bernoulli's "utility." Instead, utility was to be defined only for money under risk. Thus, a von Neumann and Morgenstern utility function not only measured a person's subjective value for money, but also, in a way that could not be separated out, measured the person's attitude toward risk.

We have, then, two different kinds of "utility" theory. Although Bernoulli's notion of utility has been largely rejected by economists as "meaningless" (Arrow, 1951, p. 425), "mystical" (Savage, 1972, p. 94), and "nonsensical" (Savage, 1972, p. 96), it might nevertheless be acceptable to psychologists given its close resemblance to a psychophysical function. Can it, however, provide an adequate psychological explanation of people's judgments and preferences in laboratory studies of risk? In my judgment the answer is no, for two reasons. The first, curiously enough, is that expected utility theory works too well for the "utility" involved to be Bernoullian utility. The problem is that, even when utility is measured using relatively small ranges of values, the functions obtained are, nonetheless, clearly curved. For example, Davidson, Suppes, and Siegel (1957) found predominately curved utility functions in a group of 15 subjects when they measured the utility of monetary values ranging between ± 50 cents. This is problematical since the range over which Bernoullian utility must be defined is so large that one would hardly expect to detect the curvature in such a restricted stimulus range.

The second problem is that when people describe their preferences for different kinds of risks, they seldom mention anything to do with the subjective magnitudes of the monetary amounts involved. Thus, no matter how true Bernoulli's observation concerning the subjective worth of money may be, people do not justify their choices on the basis of nonlinearities in utility. Instead, they tend to describe their preferences in terms of the raw amounts and probabilities involved in the gambles, particularly the probabilities (Hershey & Schoemaker, 1980; Payne & Braunstein, 1971; Schoemaker, 1982). Thus, it would appear that something like "risk attitude" must be entering the picture.

Does this mean that modern utility theory can provide an adequate psychological theory of risk? Again, I think not. The reason is that, in the modern view, utility functions are more nearly summaries of a person's preferences than they are descriptions of a person's risk processing mechanisms. To wit, a utility function is said to account for a person's preferences when those preferences can be regenerated by substituting utility values for dollar values and then choosing whatever gamble maximizes expected utility. But the utility function itself is no more than a curve that relates utility to monetary value. Thus, although a utility function may implicitly capture a person's risk attitudes, the function itself does not represent the attitudes explicitly.

The view taken here is that distributional variables are absolutely central in risk processing. This is the main strength of the distributional model of risk -- that it focuses on the distributional questions and provides the beginning of a formalism for describing distributional preferences. However, the model has several additional features that deserve at least brief note.

To begin with, since the model is stated in terms of objective rather than subjective values, it forces us to do without the excessive freedom that is introduced into the model testing process when utilities and subjective probabilities are assumed to operate. Note that I do not mean to deny that subjective values are important. No doubt a complete theory of risk would have to take account of both the distinction between monetary value and utility and the distinction between objective probabilities and subjective probabilities (or weights). However, I am fundamentally in agreement with Allais (1952/1979) that these factors are less important than distributional factors and ought to be set aside until more is known about distributional processing per se.

Second, the model seems equally capable of handling both choices between risks and judgments of riskiness. This is due in part to the fact that the model, like Coombs' portfolio theory (1975), implicitly assumes that "choice among risky decisions is a compromise between maximizing expected value and optimizing the level of risk" (Coombs, 1975, p.66). However, unlike Coombs' theory, the nature of risk is not left undefined, but rather is theoretically linked to a specified notion of distributional inequality.

Third, the model gives a reasonably simple account of how certain statistical properties of risks such as variance and skewness come to affect people's judgments and preferences. In the model, variance and skewness (together with the other moments of a distribution) contribute to a distribution's cumulative properties, which, in turn, are assumed to be what people process in risky decision making. This cumulative view can be contrasted with a model of risk processing based directly on statistical moments. In order to account for the present data using such a "moments model," one would have to assume not only that people construe risks in terms of functionally independent properties that are analogous to variance and skewness, but also that they subsequently integrate these separate properties into an overall judgment when they judge or choose among risks. Although such a view might seem unremarkable to psychologists for whom the statistical concepts of variance and skewness are familiar, it is not obvious that naive people would think of risks in terms of the squared and cubed deviations of individual outcomes about the mean outcome.

Finally, the model offers at least the potential for describing risk attitudes in terms of a unitary parameter such as the ε parameter in Atkinson's (1970,1975) index. In principle, one might use changes in the value of such a parameter to describe the effects on risk attitude of motivational set, bankroll, ambiguity, training and other psychological factors that ought to affect risky decision making. For example, there is evidence that in situations of high ambiguity people tend toward choice strategies that attempt to guarantee a reasonable "security level" (Ellsberg, 1961). Such strategies have something of the character of "maximin" solutions in which one maxmizes the minimum gain, but they do not require the sort of foolishly conservative behavior that would follow from adherence to a strict maximin criterion. The distributional model would account for such tendencies in terms of the weight attached to outcomes at the low end of the distribution. In terms of Atkinson's index, the degree of conservatism could range from strict maximining (ε equal infinity in Atkinson's index) to total disregard of minimum outcome (ε equal to zero).

In closing, the distributional model seems to offer the potential of capturing in a psychologically acceptable way many interesting and important

features of people's processing of and preference for risks. Although the model is far from a complete theory for the psychology of risk, it provides a reasonable starting place. The model may not be a sure thing, but neither is it a long shot.

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Footnotes

1. In graphical terms, the Gini coefficient is equal to the area between the Lorenz curve and the diagonal divided by the total area under the diagonal. Computationally, it is equal to half the expected percentage of difference between the incomes of two persons when those incomes are expressed as percentages of the average income.

2. An alternative way to think about the Lorenz curve for a lottery is that it plots the cumulative proportion of the expected value accruing to cumulative segments of the population. Thus, toward the EV of $100 for the lottery in Figure 2, $0 or 0% of $100 accrues to the least well off 1% of players, $2.31 or 2.3% of $100 accrues to the least well off 8% of players, and so forth.

3. I do not intend to imply that people's beliefs about luck <u>may</u> not influence their judgments, only that they <u>should</u> not. It is interesting to note that a similar normative principle is found in welfare economics. This is the principle that one's sense of what is fair should not be based on one's own position in society (Harsanyi, 1953; Rawls, 1971). Instead, judgments of social justice should be made as though the judge "had to choose a particular income distribution in complete ignorance of what his own relative position...would be within the system chosen" (Harsanyi, 1953, p. 434-435).

4. These subjects displayed preferences which ranged from mild risk aversion through mild risk seeking. Although their data were perfectly acceptable individually, they were excluded from the analysis in order not to muddy the theoretically more interesting patterns of strong risk aversion and strong risk seeking that are displayed in Figures 6 and 7.

5. It is technically inappropriate to compute between-group statistics in this case since subjects were classified originally on the basis of whether they supported the hypothesis qualitatively or not. Nevertheless, the magnitudes of the F ratios plus the large differences in choice proportions together make clear that these disagreements between subjects are reliable and systematic.

6. Kahneman and Tversky (1979) originally demonstrated the reflection effect with two-outcome gambles. Research in progress with the present set of multi-outcome distributions suggests that they also will yield switches of preference for gains and losses.

7. Research by Kahneman and Tversky (1979) suggests that, when absolute amounts are held constant, losses have a larger psychological impact than gains. Such an effect might reflect a difference in the strength of affective responses to losses and gains, but it need not. Instead, it might reflect differences in how or where the aspiration level is set.

8. Speaking of aspiration <u>level</u> tends to suggest that the value is discrete. It is probably more accurate to suppose that aspiration levels are fuzzy (Zadeh, 1965) and that a particular outcome satisfies a level more or

less well. Thus, if I aspire to win about \$100, I will not be devastated if I win only \$95.

Tables

Table 1

Income distribution in the United Kingdom, the Netherlands, and West Germany

Cumulative share of bottom %	United Kingdom 1964	Netherlands 1962	West Germany 1964
10	2.0	1.3	2.1
20	5.1	4.0	5.3
30	9.3	8.2	10.0
40	15.3	14.0	15.4
50	22.8	21.4	21.9
60	31.9	30.0	29.1
70	42.9	40.0	37.5
80	55.8	51.6	47.1
90	70.7	66.2	58.6

Note. From the Economics of Inequality (p. 46) by A. B. Atkinson, 1975, Oxford: Clarendon Press.

Table 2

Cumulative Data for Sample Lottery

Cumulative proportion of cases from bottom	Cumulative winnings	Cumulative proportion of winnings
.01	\$ 0	.000
.08	\$ 231	.023
.34	\$ 1,973	.197
.66	\$ 5,173	.517
.92	\$ 8,631	.863
.99	\$ 9,800	.980
1.00	\$10,000	1.000

Table 3

Average choice proportions for

Experiments 1-6

	Preference data				Riskiness data			
	Risk averse Ss		Risk seeking Ss					
Stimulus	Exp. 1	Exp. 2	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6
ST	.96	.93	.16	.16	-	-	-	-
VP	.64	.58	.50	.50	.32	.44	.31	.37
-L/LV	.61	.49	.48	.48	.28	.44	.34	.41
-S/LV	.57	.45	.40	.49	.24	.45	.27	.38
P	.56	.46	.52	.60	.40	.50	.40	.51
RC	.54	.44	.60	.63	.43	.46	.46	.46
-G/LV	.44	.28	.43	.42	.42	.60	.37	.49
+G/HV	.35	-	.63	-	.76	-	.68	-
+L/HV	.30	-	.60	-	.72	-	.69	-
BM	.29	.34	.52	.61	.59	.68	.67	.62
+S/HV	.25	-	.65	-	.84	-	.81	-
+S/LV	-	.62	-	.64	-	.40	-	.53
+L/LV	-	.50	-	.47	-	.49	-	.61
+G/LV	-	.40	-	.50	-	.55	-	.62

Note. Stimuli are listed in the order of preference given by risk averse subjects in Experiment 1 (first 11 stimuli) and Experiment 2 (last 3 stimuli).

Figures

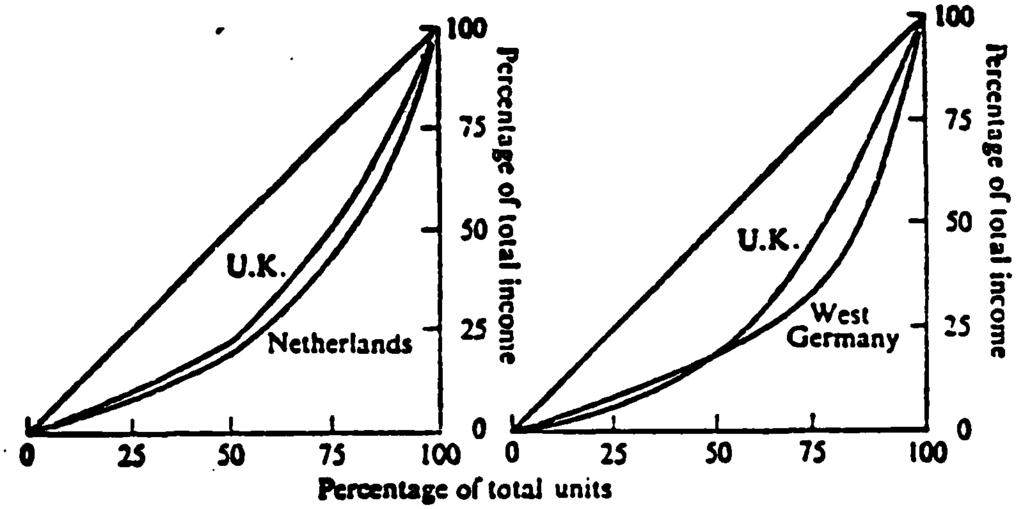

Fig. 1. Lorenz curves for the data in Table 1. From The Economics of Inequality (p. 46) by A. B. Atkinson, 1975, Oxford: Clarendon Press. Copyright 1975 by Oxford University Press. Reprinted by permission.

```
$200    #
$167    #######
$133    ##########################
$100    ################################
$ 67    ##########################
$ 33    #######
ZERO    #
```

Fig. 2. Example of stimulus lottery. Each # represents one lottery ticket. The dollar amounts represent the size of the prize won by each of the tickets in the row.

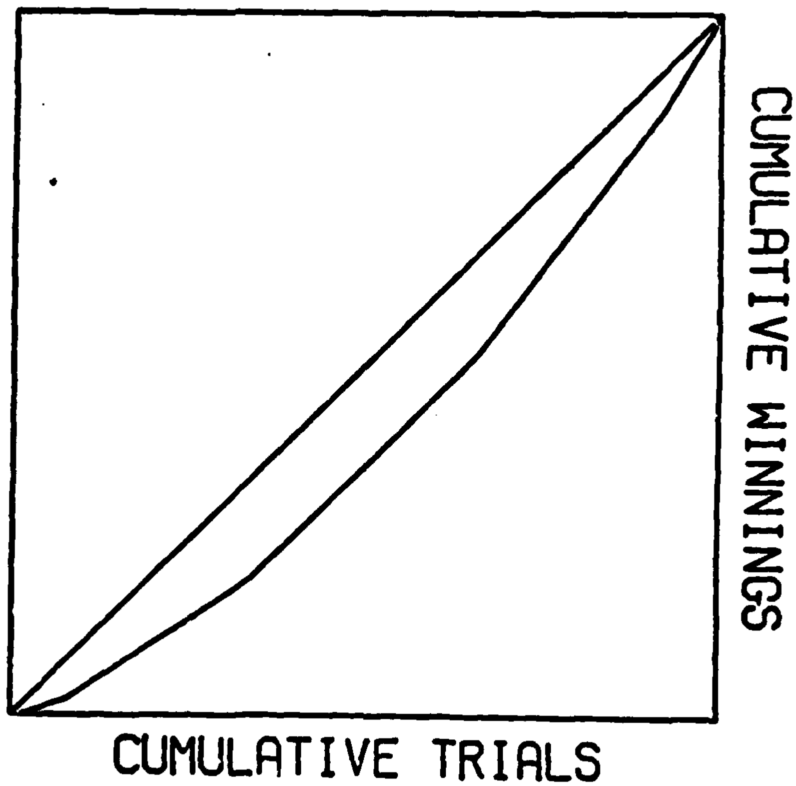

Fig. 3. Lorenz curve representation of stimulus lottery shown in Figure 2. The abscissa shows cumulative trials played by independent players and the ordinate shows cumulative winnings.

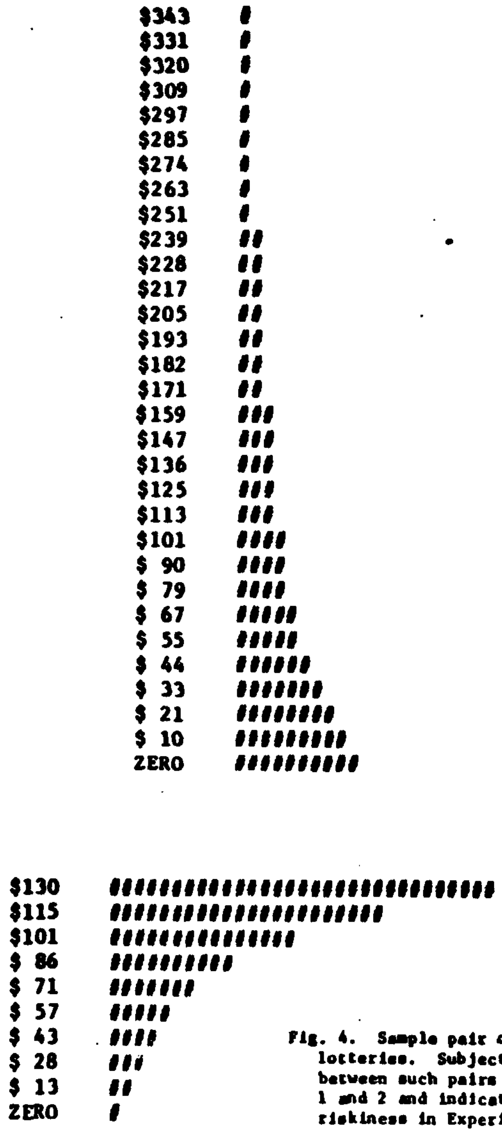

Fig. 4. Sample pair of stimulus lotteries. Subjects choose between such pairs in Experiments 1 and 2 and indicated relative riskiness in Experiments 3 through 6.

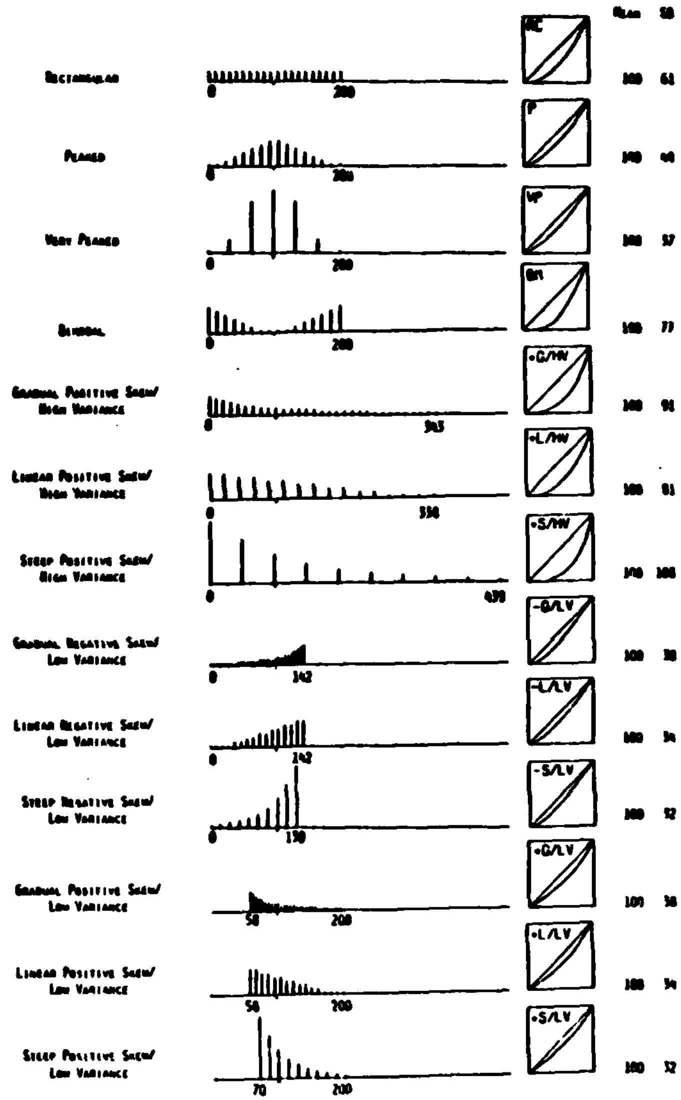

Fig. 5. Schematic representation of the set of stimulus lotteries. Actual lotteries were presented to subjects in the form shown in Figures 2 and 4.

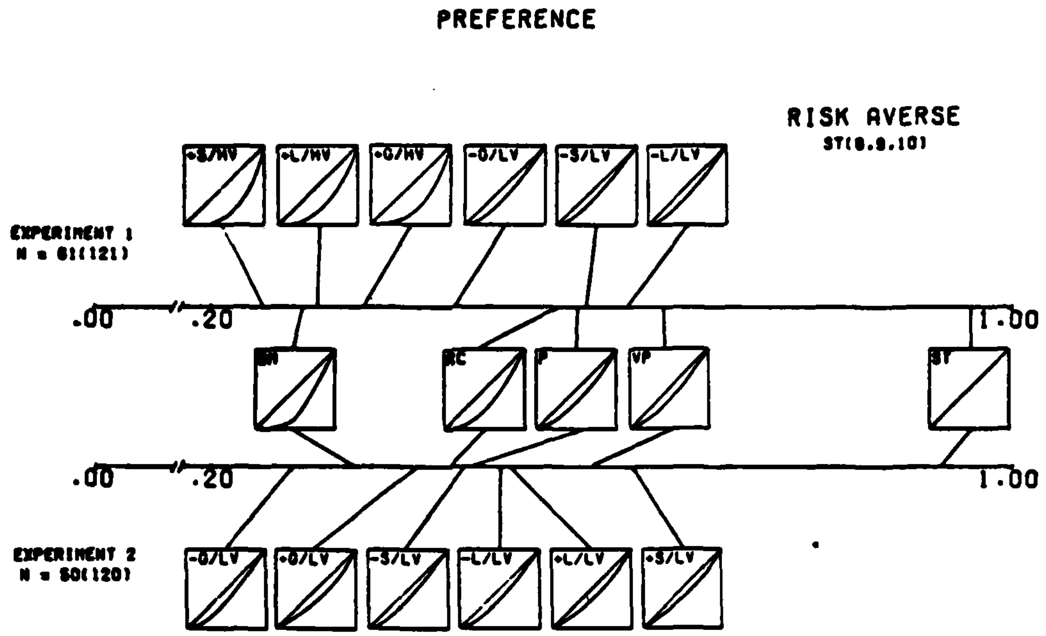

Fig. 6. Preference data for risk averse subjects in Experiment 1 (upper number line) and Experiment 2 (lower number line). Points on the number line represent the proportion of times on which the indicated lottery was preferred.

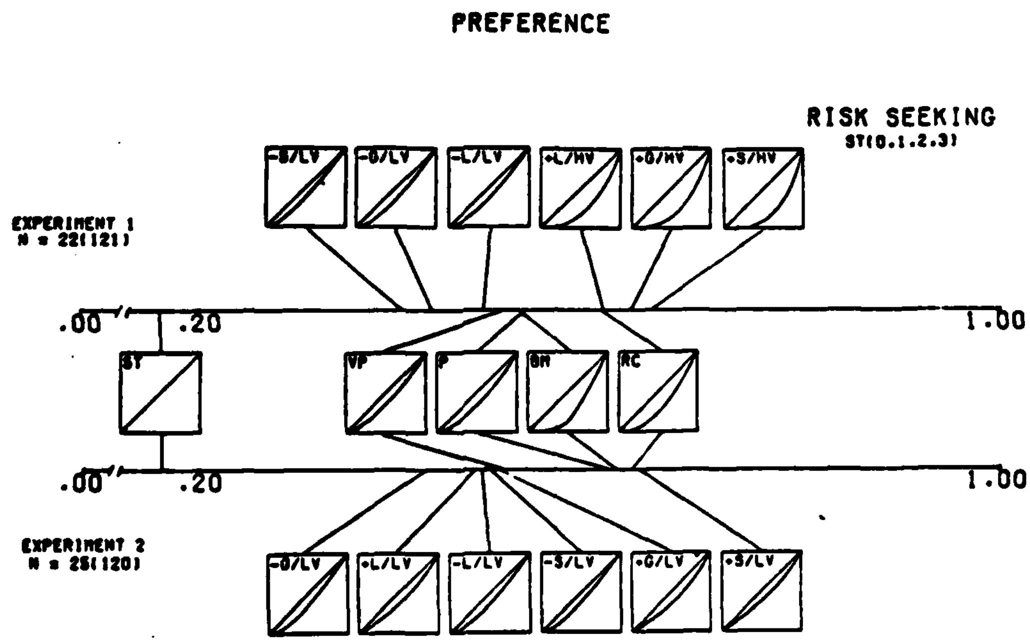

Fig. 7. Preference data for risk seeking subjects in Experiment 1 (upper number line) and Experiment 2 (lower number line). Points on the number line represent the proportion of times on which the indicated lottery was preferred.

```
$130     ###############################
$115     ######################
$101     ###############
$ 86     ##########
$ 71     #######
$ 57     #####
$ 43     ####
$ 28     ###
$ 13     ##
ZERO     #


$200     #
$187     ##
$172     ###
$157     ####
$143     #####
$129     #######
$114     ##########
$ 97     ###############
$ 85     ######################
$ 70     ###############################
```

Fig. 8. Sample pair of positively and negatively skewed lotteries with mean and variance matched.

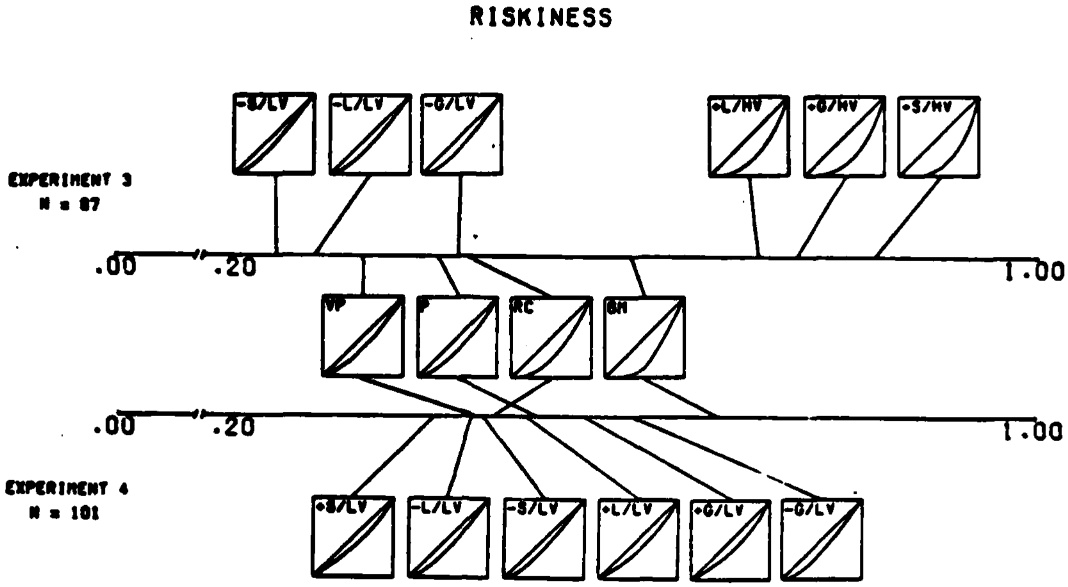

Fig. 9. Judgments of riskiness for Experiment 3 (upper number line) and Experiment 4 (lower number line). Points on the number line represent the proportion of times on which the indicated lottery was judged most risky.

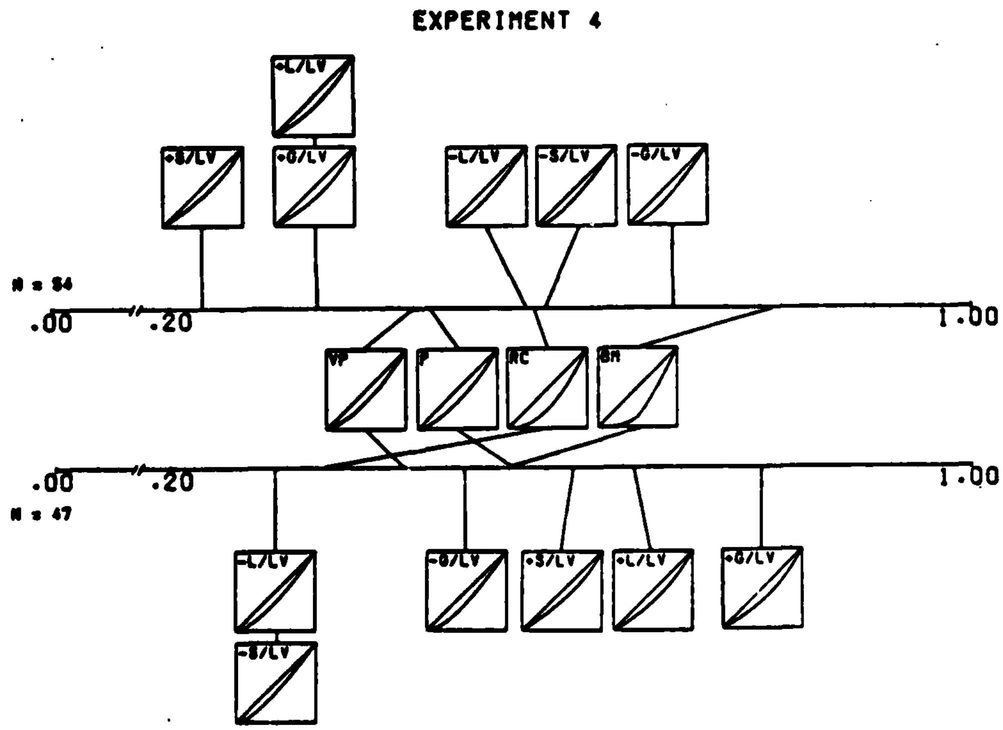

Fig. 10. Data from Experiment 4 with subjects divided according to whether they rated negatively skewed lotteries (upper number line) or positively skewed lotteries (lower number line) as most risky.

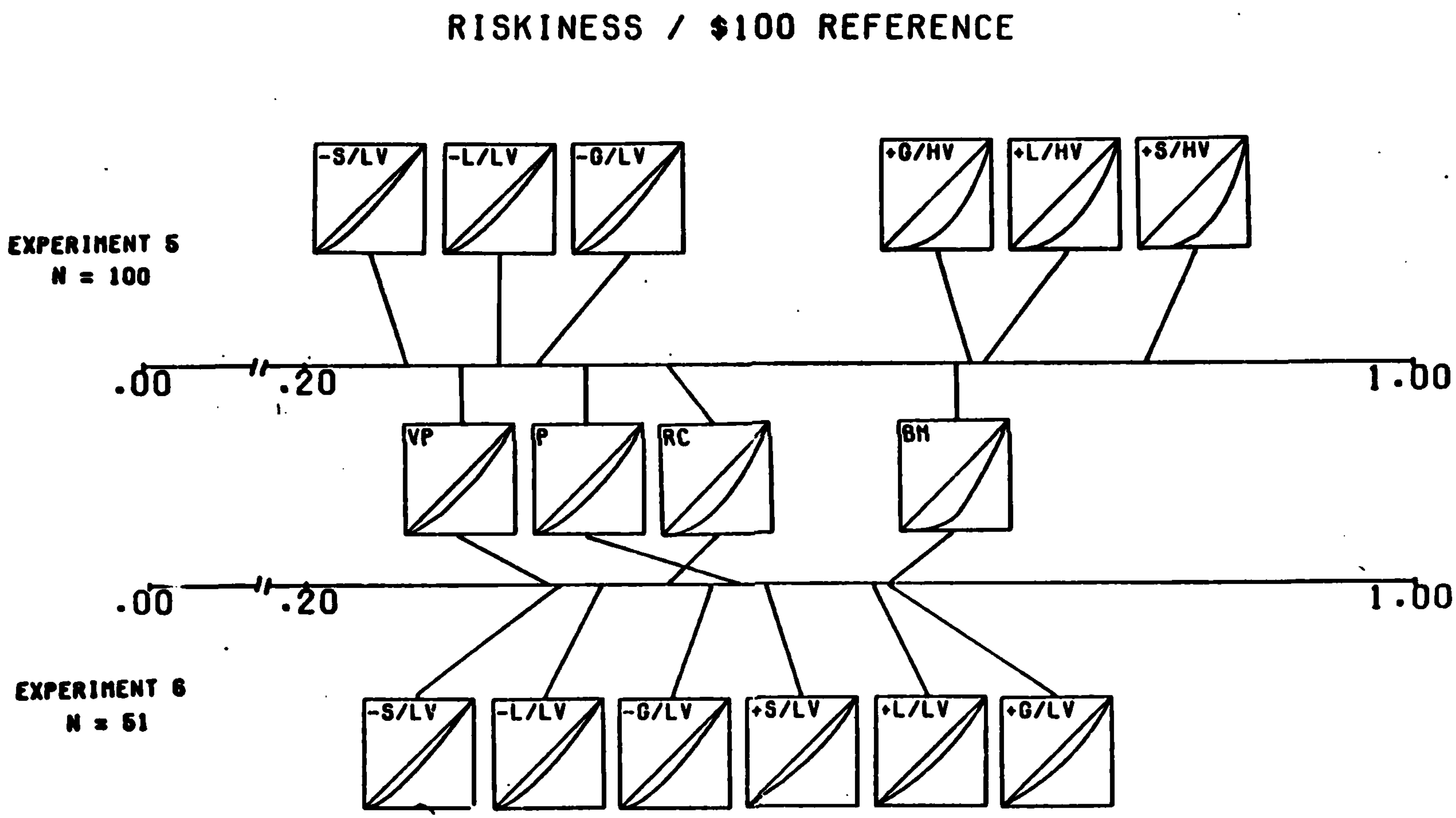

Fig. 11. Judgments of riskiness for Experiment 5 (upper number line) and Experiment 6 (lower number line). Points on the number line represent the proportion of times on which the indicated lottery was judged most risky given the $100 reference point.

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